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Technical Document 1318
July 1988

An Artificial Neural System for Autonomous Undersea Vehicles

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ADMINISTRATIVE INFORMATION

This task was performed for the Office of Chief of Naval Research, Arlington, VA 22217, with in-house funds under NOSC project ZE62. The report was first presented as a paper at the first annual Independent Research/Independent Exploratory Development (IR/IED) Symposium, 20 - 22 June 1988, at Johns Hopkins University, Applied Physics Laboratory, Laurel, MD.

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SECURITY CLASSIFICATION OF THIS PAGE

REPORT DOCUMENTATION PAGE

1a. REPORT SECURITY CLASSIFICATION UNCLASSIFIED			1b. RESTRICTIVE MARKINGS	
2a. SECURITY CLASSIFICATION AUTHORITY			3. DISTRIBUTION/AVAILABILITY OF REPORT Approved for public release; distribution is unlimited.	
2b. DECLASSIFICATION/DOWNGRADING SCHEDULE				
4. PERFORMING ORGANIZATION REPORT NUMBER(S) NOSC TD 1318			5. MONITORING ORGANIZATION REPORT NUMBER(S)	
6a. NAME OF PERFORMING ORGANIZATION Naval Ocean Systems Center		6b. OFFICE SYMBOL (If applicable) Code 943	7a. NAME OF MONITORING ORGANIZATION	
6c. ADDRESS (City, State and ZIP Code) San Diego, CA 92152-5000			7b. ADDRESS (City, State and ZIP Code)	
8a. NAME OF FUNDING/SPONSORING ORGANIZATION Office of Chief of Naval Research (OCNR)		8b. OFFICE SYMBOL (If applicable) OCNR-20T	9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER	
8c. ADDRESS (City, State and ZIP Code) Arlington, VA 22217			10. SOURCE OF FUNDING NUMBERS	
			PROGRAM ELEMENT NO. 62936N	PROJECT NO. ZE62
			TASK NO.	AGENCY ACCESSION NO. DN308 041
11. TITLE (Include Security Classification) AN ARTIFICIAL NEURAL SYSTEM FOR AUTONOMOUS UNDERSEA VEHICLES				
12. PERSONAL AUTHOR(S) M. R. Blackburn, H. G. Nguyen				
13a. TYPE OF REPORT		13b. TIME COVERED FROM TO		15. PAGE COUNT 16
16. SUPPLEMENTARY NOTATION				
17. COSATI CODES			18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number)	
FIELD	GROUP	SUB-GROUP	Artificial Neural Systems; Autonomous Undersea Vehicles; Neural Networks <i>du</i>	
19. ABSTRACT (Continue on reverse if necessary and identify by block number)				
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20. DISTRIBUTION/AVAILABILITY OF ABSTRACT <input type="checkbox"/> UNCLASSIFIED/UNLIMITED <input checked="" type="checkbox"/> SAME AS RPT <input type="checkbox"/> DTIC USERS			21. ABSTRACT SECURITY CLASSIFICATION UNCLASSIFIED	
22a. NAME OF RESPONSIBLE PERSON M. R. Blackburn			22b. TELEPHONE (Include Area Code) (619) 553-1904	22c. OFFICE SYMBOL Code 943

DD FORM 1473, 84 JAN

83 APR EDITION MAY BE USED UNTIL EXHAUSTED
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ABSTRACT

This paper introduces a new approach to the problem of information processing in autonomous undersea vehicles (AUVs). The approach involves the emulation of biological mechanisms of intelligence, principally through the evolutionary design of neural networks and systems of interacting networks, for implementation in software, parallel hardware, and analog/digital very-large-scale integration (VLSI). The objectives of artificial neural systems (ANS), in common with other AI approaches, are to provide real-time, operator-independent, pattern recognition, task planning, and adaptive AUV control for many of the underwater tasks currently being performed by man. The ANS approach emphasizes the development of autonomous intelligence capabilities through the progressive expansion of processing centers that define, orchestrate, and control basic reflexes.

An example of this approach is our current IED project in machine visual motion analysis. The perception of motion is well developed in animals from insects to man, providing critical information for obstacle avoidance and predator and prey recognition. We have therefore applied a model of the motion analysis subnetwork in the vertebrate retina to visual navigation in the AUV. The model is currently implemented in the C programming language as a discrete-time serial approximation of a continuous-time parallel process. Running on an IBM-PC/AT with digitized video camera images, the system can detect and describe motion in a 16- by 16-receptor field at the rate of 4 updates per second. The system responds accurately to images with different speeds and directions at signal-to-noise ratios greater than three. The architecture is quite simple and thus appropriate for implementation in VLSI optoelectronics.

INTRODUCTION

PROBLEM

Within the next 20 years, the Navy will need a new class of vehicles that are small, inexpensive, reliable, and capable of extended missions without human control, supervision, or intervention. These autonomous underwater vehicles (AUVs) will find significant employment in undersea surveillance, deep-sea exploration, salvage, and mine countermeasures. These applications are well recognized, and work at the Naval Ocean Systems Center (NOSC) over the last decade has progressed toward their achievement. Products include tethered and teleoperated submersibles, semiautonomous vehicles with on-board computers for navigation, pattern recognition, and vehicle control, fiber-optic data links, and untethered acoustic links supporting high-level communication.

Figure 1 shows three representative NOSC undersea vehicles. Tethered submersibles like the Mine Neutralization System (MNS) have provided remote operation capability, but suffer from the drag and short range of an umbilical cable. On-board energy supply, a supervisory-control software architecture, and single-strand fiber-optic data link increased the freedom of movement and range for the Experimental Autonomous Vehicle (EAVE-WEST). Acoustic telemetry was developed for the Advanced Unmanned Search System (AUSS) program which cut the physical link altogether. The loss of the hard wire umbilical cables in these two later systems, however, forced the vehicles to carry their own energy supply, thus limiting the duration of work.

In spite of the on-board computers, the submersibles still could not function independently of supervisory control, and that control was itself labor intensive. The von Neumann computer architectures are ill-suited to the parallel data processing requirements associated with pattern recognition, data fusion, task planning and adaptive control, and the number of lines of software code being written to address those issues face a combinatorial explosion. Thus, there remain two major problems that stand in the way of the realization of true autonomous submersibles. One is an energy source or renewal strategy that will sustain long-term voyages; the other is an effective on-board computer that will replace the control, pattern recognition, and task planning functions of human operators. This paper will focus on a new approach to the problem of on-board computation.

APPROACH

Our effort to develop AUVs is in many ways analogous to natural evolution. We are fortunate to be operating in a relatively uncomplicated environment. The ocean is homogeneous, there is little to bump into, and those objects which are moving are moving slowly. Our performance requirements are similarly simple. Current vehicles are asked only to track, to find, to fetch, or to avoid. These abilities are present in some of the simplest marine invertebrates (species lacking a backbone), which to the same degree are autonomous. Yet comparable abilities have not been attained by any class of autonomous machine using any technology available to date. Our approach therefore is to examine the methods used by marine species over the course of phylogenetic development to meet their evolving behavioral requirements. A judicious emulation of these methods, also using an evolutionary approach, should provide a good foundation for the types of artificial systems that are required for Navy missions.

There is a rich source of information available from the fields of neuroethology and behavioral neurobiology on the behavioral competence of marine invertebrates and some of the neural networks and mechanisms that generate those adaptive behaviors.^{1,2,3,4} The fourth column of Table I lists the increasing complexity of behavior across a number of species, while the third column lists new features of the nervous systems that likely support the advances in capability. Note that at the various levels of the phylogenetic scale one can find homing, tracking, predation, escape and evasion, migration, pattern recognition, learning, and memory. All are desirable functions for autonomous submersibles.



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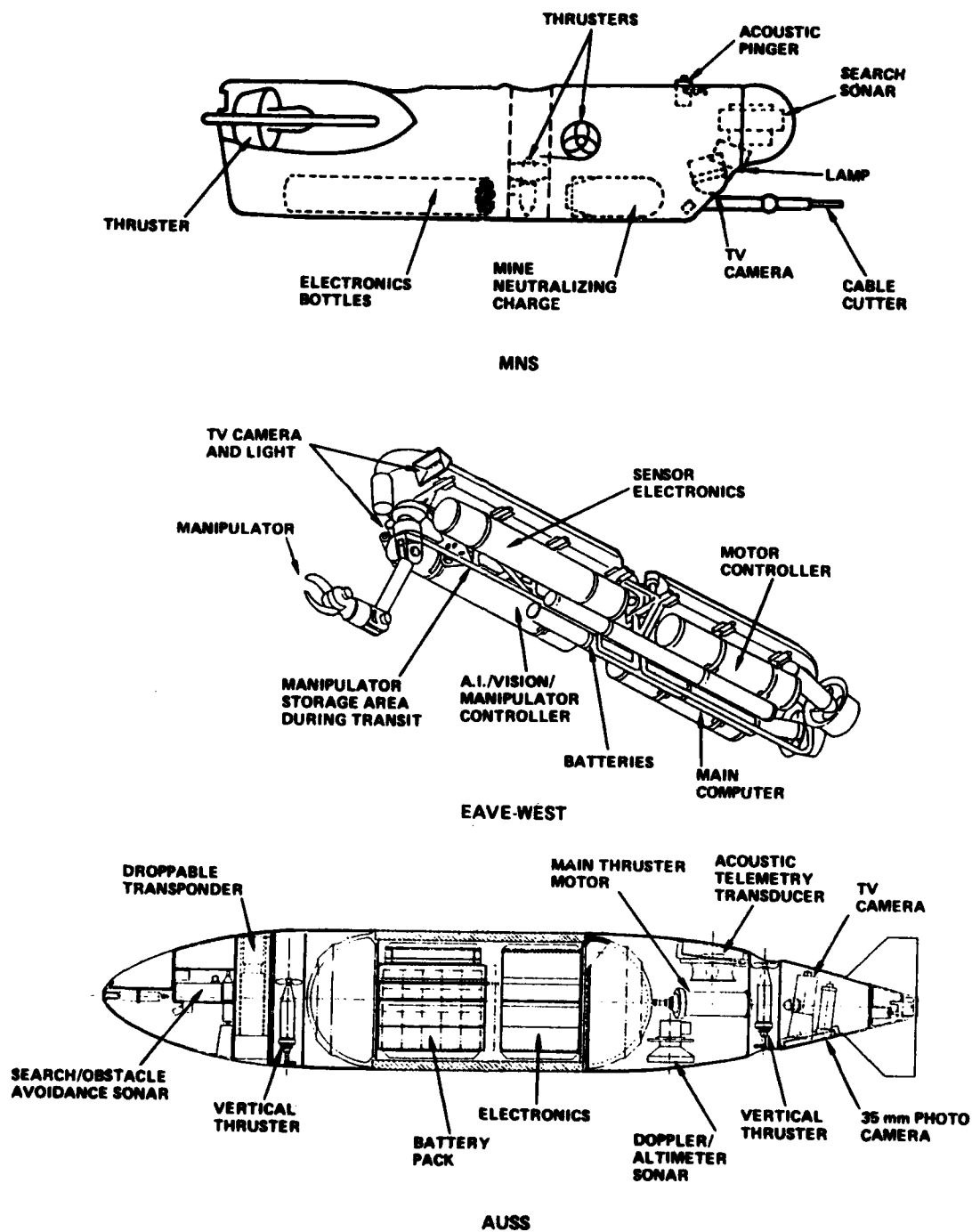


Figure 1. Three examples of NOSC unmanned undersea vehicles.

Table I. Phylogenetic Scale.

Phylum	Example	Advance	Ability
Protozoa	Paramecium	No Nervous System	Swim Food Discrimination
Coelenterata	Hydra Anemone Jellyfish	Nerve Nets Statolith	Spontaneity Righting Escape
Flatworms	Planaria	Bilateral Symmetry Head Ganglion Commissures Multisensors	Kinesis Taxis Conditioning
Roundworms	Leech Earthworm	Dorsal Brain Segmental Ganglia Central Cord Sense Organs Giant Fibers	Maze Learning
Arthropods	Shrimp Lobster Spider Cockroach Bee	Stomatogastric and Heart Ganglia Neurosecretory Cells Mixed Sensor and Motor Nerves	Startle Response Communication and Social Behavior Migration Selective Predation
Mollusks	Snail Aplysia Octopus	Brain Lobes: Centers for Special Senses, Motor, and Integration	Short- and Long-term Memory

It is instructive to examine how nature has developed these capabilities. First, basic reflexes were established to orient the animal to critical features in its environment, such as light, gravity, and sources of energy. These basic reflexes can be found in all nervous systems from the jellyfish to man, and provide the foundation for all more complicated behaviors. The organized species-specific behaviors such as mating and nest building, and the acquired behaviors such as language and art, are produced through the modulation and coordination of existing innate reflexes. Without the basic reflexes, the more complicated behavior would not be possible. Reflexes also function semi-independently to regulate internal conditions, correct for gravity and other unexpected forces, and avoid hazards. These reflexes can maintain life-support functions when the central controllers are distracted or disabled - an excellent design feature for a battle-hardened system.

PROSPECTS FOR AN ARTIFICIAL NEURAL SYSTEM

A major difficulty of the artificial neural systems (ANS) approach is the lack of an appropriate hardware for implementation. While much work is going on in this area,⁵ there are no generally available neural computers that run networks in parallel and do not consult a program of stored instructions.

Asking for such a computer may be the wrong approach. The success of biological neural networks stems from the appropriateness of their design to the environment, and to the sensor and effector equipment of their species. The common design features shared by most biological neural systems can be attributed to a common environment and to similar equipment. When more processing was required to survive in a varied environment, the earlier design was not abandoned; it was simply expanded. An increasingly complex biological neural system was developed by building hierarchical control and integration systems on existing more primitive components. All biological neural systems are highly organized assemblies of functionally differentiated components, just as a piece of electronic equipment is assembled from discrete components. These components, however, when modeled after biological neural networks, would manifest well-known advantages of fault tolerance, ambiguity tolerance, speed, and adaptability that are consequences of distributed parallel processing. An artificial neural computer should be similarly constructed. Instead of an unstructured collection of homogeneous processing elements, to be rewired for each different application, the neural computer should be assembled from tuned circuits. These circuits should have a functional specificity, but also have a certain degree of interchangeability from one neural computer to the next. Why this has not happened can be attributed to the lack of good functional components. There are no off-the-shelf analogues of the retina (early vision), optic tectum (visual motor control), hypothalamus (internal state monitor and controller), or locus coeruleus (arousal). Our program is an effort to provide those components and assemble them into working control systems. An application of this approach to visual motion analysis for AUVs will be described next.

MODEL OF MOTION ANALYSIS IN VERTEBRATE RETINA

The purpose of machine vision is to provide information on the relative location, change in location or movement, and distinguishing characteristics of objects in the visual field. This information will be used by a vehicle in the performance of some physical work, such as navigation, search and recovery, or repair. To do so, the visual system must provide input and feedback to vehicle effector controllers. Additionally, autonomy dictates that the visual processing must take place on the vehicle, and a free-swimming vehicle requires that the visual processing take place in real time. To date, there have been few successes in the development of an on-board machine vision system that provides real-time analysis of motion for a moving vehicle.

In contrast to our difficulties with machine vision, most marine animals have solutions to vision requirements under water. These range from light-sensitive spots that allow orienting, to complex retinal and cortical processing of form, color, and motion. The compound eyes of arthropods, including flies, beetles, lobsters, and crabs, are designed primarily to detect motion,⁶ and while the vertebrate visual system has advanced pattern analysis across the phylogenetic scale, it has remained extremely sensitive to movement.⁷

MOTION ANALYSIS IN THE VERTEBRATE RETINA

The neural connectivity of the vertebrate retina has been studied extensively,^{8,9,10,11} so there is much to draw upon in the construction of a model. It appears that visual systems are organized to perform two complementary visual processes. One involves pattern and color, the other involves motion and spatial relationships.^{11,12} The neural mechanisms of these two basic processes are evidently distinct in the retinal architecture and remain separable far into the cerebral cortex.¹³ Interactions of these two processes are likely, but are unnecessary for the level of performance required of the present model.

Pattern and color analysis in the vertebrate retina is initiated by a network involving cone receptors and sustained-activity X-type ganglion cells. Motion analysis begins in the retina with a network involving rod receptors and transient-activity Y-type ganglion cells.¹⁴ While the cone/X-type ganglion cell circuit exists side by side with the rod/Y-type ganglion cell circuit, the fact that the two types of image processing networks are distinct eases the degree of retinal complexity to which we must attend. Our model thus focuses on the rod to Y-ganglion cell subnetwork for motion analysis.

Between the rods and Y-ganglion cells of the motion analysis subnetwork are beta horizontals, rod bipolars, and more than one type of amacrine cell.¹⁵ This subnetwork is shown schematically in Fig. 2. The beta horizontals receive input from several rod receptors¹⁵ and inhibit rod bipolars.¹⁶ The rod bipolars communicate with the two types of amacrine cells. The first type is a low density but large diameter receptive field cholinergic amacrine (A-I) interposed between the rod bipolar and Y-ganglion cells.¹⁷ The second type of amacrine (A-II) has a higher density in the retina but each cell has a smaller diameter receptive field than the A-I amacrine.

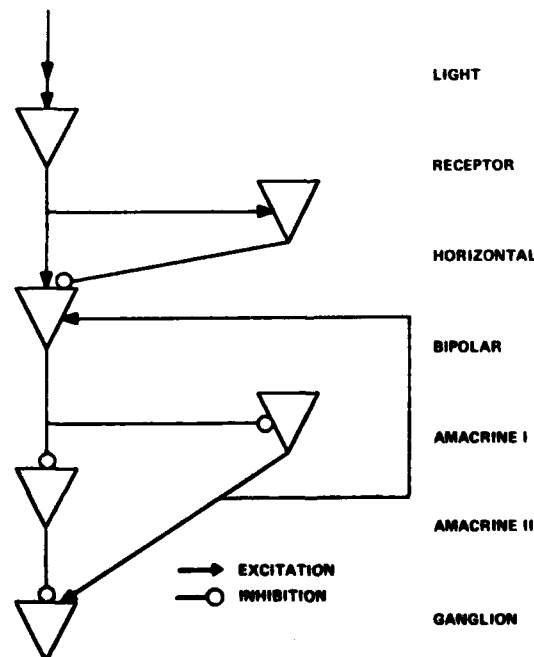


Figure 2. Biological model of motion analysis sub-network in vertebrate retina.

The neurotransmitter of the A-II amacrine is likely gamma-aminobutyric acid (GABA), a known inhibitor. Pharmacological blockade of this neurotransmitter by picrotoxin was found to eliminate the null response of direction selectivity (defined in the next paragraph) in the rabbit retina.¹⁸ Rod bipolars converge on the A-II amacrines with a ratio of about 30:1. It is possible that the A-II amacrines inhibit the Y-ganglion cells, while the A-II amacrines themselves may be under inhibitory control from the rod bipolars.^{19,20} Masland, Mills, and Cassidy²¹ suggest that despite the large dendritic field of cholinergic (A-I) amacrine cells, their output is localized to the immediate region surrounding the bipolar input. Since the dendrites of the ganglion cells extend into the inner plexiform layer and intermingle with bipolar axon arborizations and amacrine dendritic arborizations, both types of amacrine cells have the opportunity for local control over bipolar to ganglion transmission.

DIRECTION SELECTIVITY

Direction selectivity has been recorded from retinal ganglion cells in several different species, including goldfish, frog and toad, turtle, pigeon, cat and rabbit.²² Barlow and Hill²³ reported that some ganglion cells in the rabbit responded vigorously when successive stimuli were presented in one direction across their receptive fields (the preferred direction), and decreased their activity when movement was in the opposite direction (the null direction for that ganglion cell). The receptive field is that region of the visual field to which the ganglion cell responds. It is generally concentric - encompassing up to 8 degrees of visual angle.²⁴ Barlow et al.^{24,25} proposed that direction selectivity was the result of an inhibitory mechanism that vetoed responses in the null direction.

Current thought on the mechanism for direction selectivity in the vertebrate retina (shown in Fig. 3) remains based on the convergence of excitation and inhibition at the input to the ganglion dendrite.^{11,27} The functional components of the mechanism involve only the two different types of amacrine cells: one inhibiting, and the other exciting the direction-sensitive ganglion cells. The two types are arranged spatially so that a moving image activates first one then the other. The preferred direction requires activation of excitation in advance of inhibition, while the null direction requires the converse.

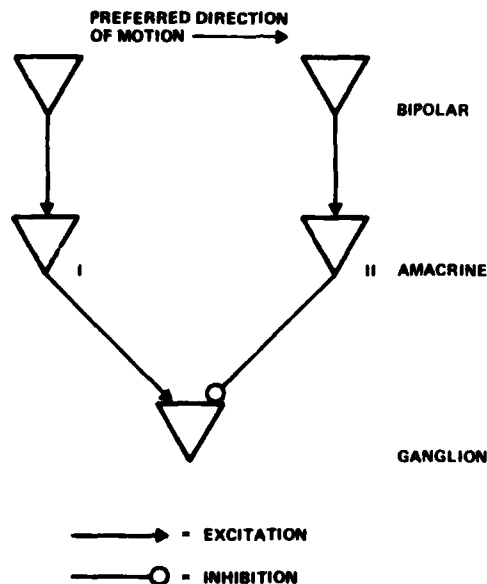


Figure 3. Mechanism of direction selectivity. Images moving from left to right generate excitation in advance of inhibition at the ganglion cell.

SYNOPSIS OF THE MODEL

There is more than one way to connect processing elements in a model retina to achieve direction selectivity. In this paper, we will describe and contrast two of our more successful variations. One method involves inhibition of bipolar to ganglion transmission (I-variant); the other involves facilitation of bipolar to ganglion transmission (F-variant).

The basic retinal model for motion processing is a feed-forward sparsely interconnected neural network, based on the models shown in Figs. 2 and 3. The connection patterns for the I and F variations of this network are shown in Figs. 4a and 4b respectively, and described below. The numbers of elements in the networks can be arbitrary, dependent only on the size and resolution of the digitized image, and on the ability of the computing machine to process the information in the required time. However, the numbers of the

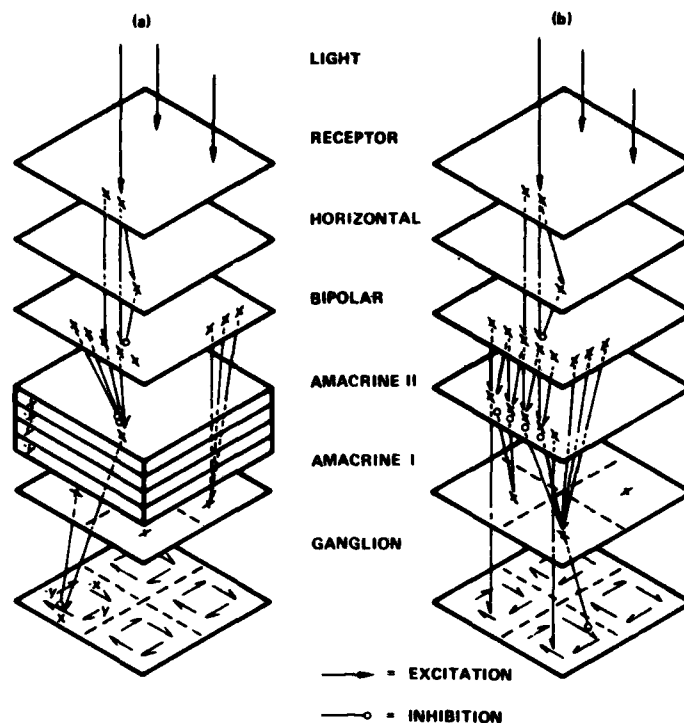


Figure 4. Two variations on the mechanism of direction selectivity. (a) Shows the use of persistent lateral inhibition to block conduction in the null direction. (b) Shows the use of persistent lateral excitation to facilitate conduction in the preferred direction.

different types of elements maintain fixed proportions to the total. There are six different types of elements, roughly analogous to receptor, horizontal, bipolar, amacrine I and II, and ganglion cells of the biological retina. Elements of like type are assembled into layers. The layers are connected by delay lines. Activity originating in the receptors percolates through the retina, delayed by one time constant (t) at some connections as noted below. The time constant in the current implementation is defined by the program cycle time.

The receptive field is divided into sectors by the convergence of an area of bipolars on A-I amacrine and of A-II amacrine on ganglion elements. As a minimum, we use four sectors which divide the visual field into four equal quadrants.

Receptor Elements. The receptor (R) matrix is represented by gray-scale values which can originate from an image simulator or a frame grabber that has digitized television camera images or a matrix from some other sensor. Simulator and frame grabber values range between 0 and 256. Higher numbers are associated with brighter light. These values are forwarded to horizontal and bipolar matrices in columnar pathways.

Horizontal Elements. Horizontal (H) elements receive input without delay from the nearest receptor located immediately above.

$$H_{ij}(t) = R_{ij}(t)$$

where i indexes the position on the X axis, and j indexes the position on the Y axis of a Cartesian map of the receptor surface. Horizontal element output is forwarded to the bipolar element located immediately below, after a delay of one cycle.

Bipolar Elements. Bipolar (B) elements compare the inputs from local receptor and horizontal elements, passing on the positive value of the difference. The choice of differencing is not critical for the performance of the model. Bipolar output could be made contingent upon only increases in light intensity (R-H), upon only decreases in light intensity (H-R), or upon change in either direction, derived by taking the absolute value of the difference ($|R-H|$).

$$B_{ij}(t) = H_{ij}(t-1) - R_{ij}(t)$$

$$B_{ij}(t) \text{ out} = \begin{cases} B_{ij}(t) & \text{if } B_{ij}(t) > \phi \\ \phi & \text{if } B_{ij}(t) \leq \phi \end{cases}$$

The local change in light intensity is transferred to the two types of amacrine elements. The bipolar output is passed to the A-I amacrine element in its local sector and also to the A-II amacrine elements through a connection matrix that determines sensitivity to direction of intensity change across the receptor layer.

Amacrine Elements. Type A-I amacrine (AI) elements integrate input only from bipolar elements in the local sector and send output to adjust thresholds of sector ganglion elements. A percentage (g) of A-I activity persists.

$$AI(t) = g * AI(t-1) + \sum B_{ij}(t) \text{ out}$$

It is the connectivity and functions of the A-II amacrine elements that contribute to the variation in our model of direction selectivity. In the I-variant, there is persistent inhibition in the null direction. Bipolar input accumulates and persists in A-II amacrine elements which then inhibit and block bipolar conduction to ganglion elements in the null direction. In the I-variant, each ganglion element is associated with a unique field of A-II amacrine elements (or dendritic regions of a few large amacrine elements) that store the inhibition. In the F-variant, persistent excitation in the preferred direction is used. There is only one field of amacrine elements and this is shared by each of the four direction-sensitive ganglion elements in a sector. Excitation is distributed and stored horizontally in advance of movement in the preferred direction and used to facilitate the bipolar to ganglion transmission. The differences in the two models will now be described separately, beginning with the model using persistent inhibition.

Type A-II amacrine (AII) elements sum bipolar output within small receptive fields of a sector with any residual inhibition (with a persistence factor of e). The receptive field of an A-II amacrine element is limited to bipolars lying on one axis of the X-Y plane and behind its overlying bipolar relative to the direction selectivity for that plane of elements. The bipolar's influence on the amacrine elements is subject to 1/d, where d is the horizontal distance between them. In practice, we have limited d to the value of 3.

$$AII_{Dij}(t) = e * AII_{Dij}(t-1) + \sum_{d=1}^3 B_{(i \text{ or } j) \pm d}(t) \text{ out} / d$$

where D is the direction selectivity. D determines which index (i or j) to increment (+) or decrement (-). The residual inhibition has an exponential decline and so is maximal with recent movement in the null direction.

Output to a direction-sensitive ganglion element is the bipolar activity that exceeds the local residual inhibition from the A-II amacrine associated with that direction.

$$AII_{Dij}(t) \text{ out} = \text{pos}(B_{ij}(t) \text{ out} - AII_{Dij}(t-1))$$

In the variation using persistent excitation, type A-II amacrine (AII) elements also accumulate bipolar output with a persistence factor of e.

$$AII_{ij}(t) = e * AII_{ij}(t-1) + B_{ij}(t) \text{ out}$$

but, the horizontal spread of AII potentials creates a facilitatory gate for the transmission of new bipolar activity on to the ganglion element. The sensitivity of this gate is itself modulated by a portion (f) of the sector's A-I amacrine activity.

$$AII_{Dij}(t) \text{ out} = (AII_{(i \text{ or } j)}(t-1) * B_{ij}(t) \text{ out}) / (f * AI)$$

A recent history of activity from bipolar elements on one side biases the amacrine element's sensitivity to activity from bipolar elements on the other side.

Ganglion Elements. In both variations, there are four ganglion (G) elements per sector, each defining a preferred direction (D). Each ganglion element integrates activity from all of the bipolar elements in its sector with mediation by the A-II amacrine elements, and compares that sum with a portion (h) of the accumulated potential on the A-I amacrine. Lateral inhibition between complementary ganglion elements of a sector (left vs. right, and up vs. down) prevent contradictory responses even in conditions of high noise.

$$G_D = \sum AII_{Dij} \text{ out} - \sum AII_{-Dij} \text{ out}$$

$$G_D \text{ out} = \begin{cases} 1 & \text{if } G_D > h * AI \\ \phi & \text{if } G_D \leq h * AI \end{cases}$$

The activity state of the ganglion element is set to 1 if the ganglion potential exceeds its threshold (the ganglion element fires), otherwise it is set to zero. The activity states of the ganglion elements code the network's decisions about the certainty of coherent movement in a sector of the visual field. Increasing the A-I amacrine element potential is equivalent to raising the criterion for certainty. Ganglion element activity in a sector provides location information to the resolution of the size of the sector. The speed of movement is coded in the pulse frequency of the ganglion element output. The direction of movement in a sector is determinable from the relative firing rates of the ganglion elements since they code speed of movement along orthogonal X and Y axes.

SIMULATION HARDWARE

The model was implemented in the C programming language. Simulations were performed on a Sun Microsystems workstation. An IBM/PC-AT was used with a frame-grabber to study digitized video images. The IBM-PC/AT insured compatibility with the IBM-PC/AT bus used by the laboratory's free-swimming underwater vehicle (EAVE-WEST). The field-of-view of the video camera was approximately 32 degrees. This provided 2 degrees of visual angle between the receptors using a 16- by 16-receptor field. The digitized frame of 512 by 512 was sampled at 32-pixel intervals to produce the smaller array. The IBM-PC/AT update rate with the I-variant was 2.5 frames per second while that of the F-variant was 4 frames per second. This is barely adequate for most practical real-time visual work. Comparable simulations on the Sun ran eight times as fast.

BEHAVIOR OF THE MODEL

Criteria for adequate behavior were (1) rapid fading of a stationary image, (2) increase in the output pulse rate proportional to the speed of image movement, (3) increase in x/y output asymmetry proportional to the direction of image movement off the diagonal, and (4) unambiguous response to movement with signal-to-noise ratios (S/N) of 5 or better.

The two variations of the model were tested using the parameters given in Table II.

Table II. Parameters Used in Test of Model.

Parameter	I-variant	F-variant
Amacrine I Persistence =	0.50	0.50
Amacrine II Persistence =	0.70	0.50
Amacrine I to Ganglion Gain =	0.10	0.10
Amacrine I to Amacrine II Gain =	—	0.10

Insensitivity to Stationary Images. In the present model, the horizontal elements guarantee that the image will disappear if stationary for two or more program cycles. Because the bipolars respond to the difference between the horizontals and receptors, only positive intensity differences are passed on to the amacrine. However, the model generally works well for both increases and decreases in light intensity if either brightening or dimming detection is used. This is because an inverse image trail accompanies any movement (except an expanding light region with dimming detection or an expanding dark region with brightening detection). The motion sensitivity of the model is similar to the performance of the artificial retina developed by Mead and Mahowald.²⁸ They were able to implement in VLSI the first three types of retinal cells. Our model extends this processing through to the ganglion cell layer providing information on speed and direction of movement.

Speed Sensitivity. In the absence of noise, the model reliably produced an output each time the image moved from one receptor to another. Slowly moving images simply persisted on receptors and horizontals and disappeared from bipolars until a new receptor was crossed and stimulated by a change in brightness. The integrated output of the ganglion elements was related to the speed of image movement between two limits. The lower limit resulted from the loss of A-II activity that blocked or gated the bipolar output to the ganglion layer, governed by the A-II persistence. The upper limit was due to the sampling rate of the system. The I-variant was more successful at following slowly moving images ($\ll 0.1$ degree of visual angle per second) because A-II persistence could be set at a much higher level than in the F-variant. Under high-noise conditions, the residual excitation of the F-variant acted like an indiscriminate sieve that passed most activity on through to the ganglion layer.

Direction Selectivity. Images that were moved on either the horizontal or vertical axes generated unambiguous responses from detectors aligned with the movement. Off-axis movement resulted in appropriate combinations of vertical and horizontal responses. The mechanism responsible for this effect was the relative number of receptors crossed by the moving image per unit of time. Under some conditions, however, the direction of movement defined by the relative ganglion output was orthogonal to the orientation of the leading edge of the image and bore no relationship to the true direction of movement of the center of mass of the moving object. The conditions under which this occurred, such as when the object was much larger than the visual field, prevented the determination of the object's center of gravity.

Noise Immunity. The effects of noise on the ability of the retinal model to track a moving image were explored by varying the S/N in simulations. The S/N was defined by the ratio of the contrast difference between the moving image and the mean background intensity, and the rms of the background at each sample. Background noise was random in both temporal and spatial domains but its variance was consistent over time. Figure 5 provides the error rate as a function of S/N for the two variations of the model. An error

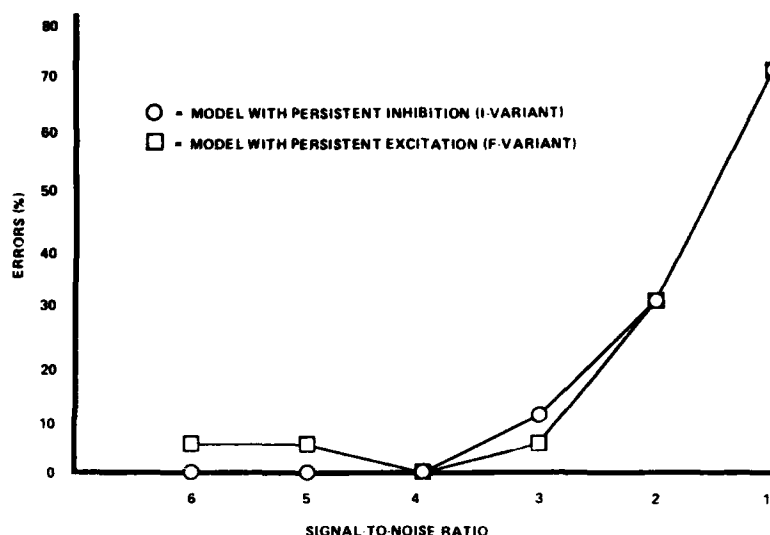


Figure 5. Errors in ganglion cell output as a function of noise.

was defined as either an omission of the appropriate response or as the commission of an inappropriate response. The target was a homogeneous line extending the full width of the visual field and moving at the maximum velocity. The error curve describes a sigmoidal relationship to S/N . In the I-variant, errors were negligible until the S/N was reduced to 4. Then the error rate accelerated to asymptote at 75%. In the F-variant, the error curve demonstrated greater accuracy than the I-variant with higher levels of noise. The F-variant was 95% accurate at a S/N of 3. The maximum error rate of 75% was reached by both variations of the model at a S/N near 1. Random firings of the 4 ganglion elements would guarantee the maximum error rate.

THE CONTEXT OF VISUAL MOTION ANALYSIS

The success of our model must be assessed by its ability to extract relevant information from the environment. This information will be used by additional processing stations to generate an appropriate motor response. Through simple reflex connections between movement detectors and motor controllers, the vehicle could seek out and orient to man-made objects such as anchor chains or pilings. Collisions with either stationary or moving objects could be avoided using the same information. The reflexes that steer a vehicle toward some feature in the visual field could be inverted to steer the vehicle away from the feature. Additional processing stations would be tasked with making the decision to approach or to avoid. One criterion for such a decision may be the velocity of closure.

Image Movement Caused by Motion of Vehicle. Movement of the vehicle in a stationary environment will cause all of the features to move on the receptor surface. If the vehicle is moving horizontally relative to a vertical line, a large response will be generated in the vertical detectors, while vertical movement of the vehicle against the same vertical line will allow it to go virtually undetected. Appropriately connected to motor controllers, the detector output will tend to keep the most significant features in the center of the visual field. This response is similar by design to the optokinetic reflex of insects that keeps them moving in straight lines and compels them to orient to high contrast edges.⁶ This behavior is extremely useful for underwater tasks such as cable tracking.

Image Movement Caused by Motions of Both Object and Vehicle. Independent movement of objects in the visual field of a moving vehicle can occur in a tracking scenario. If there are no stationary objects, then the problem of tracking is simplified to that of orienting to a moving target from a stationary platform, or to a stationary target from a moving platform, for either condition will result in similar effects in the movement analysis network. However, if both the vehicle and the target are moving in a field of stationary objects, some method must be applied to filter the motion information due to the vehicle's movement. Since collision avoidance will likely be required, this information cannot simply be discarded. Rather, the unique motions of the target must be identified. The amphibian appears to sidestep this problem by remaining motionless, or, if the environment persists in moving, by stabilizing the background movement with an opposing movement of the eyes.²⁹ An alternative to the amphibian strategy is to have a secondary motion processing station respond to the change in detector output such that the continuous motion information can be attributed to vehicle movement while deviations limited to some sectors could be attributed to target movement. For example, decelerations in all sectors indicate that the vehicle itself is slowing down, while a deceleration in one sector indicates that a target has moved. Information from other sensors such as Doppler sonar, accelerometer, or altimeter can also be used to assess vehicle movement and assist in visual fixations.

Noise Sensitivity. The test of noise sensitivity that we used simulates a noise condition in which contrast is continually changing in all directions without consistent pattern. As a well-defined image moves among these apparitions, it is degraded by loss of background contrast, and by feed-forward inhibition from activity in advance of its movement. A situation in nature comparable to this noise condition is active clutter. Backscatter in the underwater environment caused by suspended particles may generate similar conditions, but will tend to be more homogeneous or diffuse. The problem of clutter for a motion analysis system is the reason tennis is not played with more than one ball. Obviously the problem is difficult to solve even with all of the visual capability of man.

Velocity Sensitivity. In the absence of noise, the present model codes velocity of an object moving across the visual field by the frequency of action potentials generated at the ganglion elements. The maximum velocity to which the model can encode is limited by the program cycle (or update) time when running on a serial machine. This is currently four frames per second on an IBM-PC/AT. With the 16- by 16-receptor array and a 32-degree field-of-view, this translates to 8 degrees of visual angle per second. For comparison, the maximum velocity that can be tracked by a cell in the visual cortex is about 25 degrees visual angle per second.³⁰ In an implementation where it is possible to process the receptor input in parallel, output will still be proportional to velocity, but the maximum encodable velocity will be limited only by the throughput speed of the system.

At velocities below the maximum for the model, the output over time is proportional to the velocity. The system tracks slow moving objects in the absence of noise down to velocities in the range of 0.1 degree visual angle per second. For comparison, the lower limit of a cortical cell to track a moving image is about 1 minute of visual angle per second.³¹

BIOLOGICAL FIDELITY OF THE MODEL

Of the two variations of the model that we have described, the I-variant is more aligned with known biological mechanisms than the F-Variant. Several studies have shown that inhibition is necessary for the null response from direction-sensitive ganglion cells.^{32,18} The F-Variant may model the effects of thalamic efferent input to the retina. The facilitation due to excitation moving in advance of the image improved the model's recognition of image direction with noise. Both models deviate from biology by oversimplifying and omitting many details of retinal function such as rod adaptation, rod convergence, and some aspects of bipolar to amacrine and amacrine to ganglion mapping.

SUMMARY

We have described two variations on a very simple method of machine motion analysis based on a partial model of the vertebrate retina. One variation involves lateral inhibition in the null direction, while the other uses lateral facilitation in the preferred direction. The model produces an output proportional to the speed of image movement along the X and Y axes of the receptive field. Both direction and velocity are available from this information. We have noted digressions of our model from available neuro-physiological data, but offer the model as a working solution to the problem of visual motion information for guidance of autonomous vehicles, rather than as a hypothesis of biological mechanisms. We do suggest that the number of parsimonious solutions is limited, and because nature tends to exploit simple solutions, some insight into unknown biological mechanisms may be gained through this type of exploration.

CONCLUSIONS

The development of a complete ANS is an ambitious objective of science fiction proportions. Even with a century of neurobiological information waiting to be applied, and the neurosciences experiencing a heyday of discovery, the knowledge gaps are enormous. Reverse engineering of the brain will still require a lot of creativity. The prospects for success are good, however, if we start with very simple systems, where much is known, and where the behaviors or performance criteria are well defined. Yet, because of the simple performance capability of these reflex systems, a degree of patience must be exercised early on until sufficient complexity and sophistication is achieved to solve hard problems.

We have demonstrated this approach with the model of motion analysis in the vertebrate retina. This provides us with a basis upon which to move into the brain and construct an artificial visual system. But we are not just studying vision; rather we are trying to understand vision in the context of sensory/motor integration. A larger and more ecological perspective would have us consider vision in the context of the vehicle's survival in the ocean environment.

The limitations of software based simulations are obvious. Attention should be given to the rapid implementation of these designs in VLSI or other media that will sustain the highly parallel and adaptive processing. Reflex systems are ideal for VLSI because they do not generally require long-term modifications to the connection strengths, but do require their modulation. In the beginning, a feasible ANS can be envisioned with a large number of chip-resident components communicating with and supervised by a hierarchy of distributed processing machines of more conventional design. The early application of ANS will allow a survival-of-the-fittest testing under real-world conditions and further the evolutionary development of this new kind of intelligent species, the AUV.

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